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Sentiment Analysis on Social Media using Support Vector Machines (SVM)

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ABSTRACT

Sentiment analysis has become a critical tool in understanding online discussions' opinions, sentiments, and emotional tone, particularly on social media platforms. In this study, we explore sentiment analysis using Support Vector Machines (SVM) on the Sentiment140 dataset, a large-scale Twitter dataset. The Sentiment140 dataset is pre-labelled, containing tweets labelled as positive, negative, or neutral, and is widely used for sentiment classification tasks. We implement SVM, a powerful supervised learning algorithm, to classify the sentiments expressed in tweets. The study focuses on data pre-processing, feature extraction, model training, and evaluation, providing insights into how SVM can be leveraged for effective sentiment analysis in social media applications. We demonstrate that SVM, coupled with the Term Frequency-Inverse Document Frequency (TF-IDF) method, can achieve high classification accuracy in predicting tweet sentiments.

KEYWORDS: *SVM, NLP, ML, TF-IDF*

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1. INTRODUCTION

With over 400 million active users, **Twitter** has become one of the most influential social media platforms globally, where users express a wide range of opinions, thoughts, and emotions on various topics. These tweets can provide valuable insights for various stakeholders, including businesses, governments, and researchers, interested in understanding public opinion or tracking consumer sentiment.

Sentiment analysis, also known as opinion mining, is the task of determining the sentiment expressed in a given text, often classified as positive, negative, and neutral. Traditional methods of sentiment analysis include machine learning algorithms, which have been proven effective at handling large-scale data. One such algorithm is **Support Vector Machines (SVM)**, which is known for its robustness and accuracy, particularly when dealing with high-dimensional data, such as text.

The **Sentiment140 dataset**, which contains over 1.6 million labelled tweets, is widely used for sentiment analysis tasks. This dataset has been pre-labelled with sentiment categories, making it ideal for training and evaluating machine learning models. In this paper, we utilize SVM for sentiment classification on the **Sentiment140 dataset**, exploring how it can be used to classify tweet sentiments and evaluate the performance of SVM concerning accuracy, precision, recall, and F1-score.

2. Related Work

Sentiment analysis has been a widely researched area, especially in the context of social media. Many machine learning models, such as **Naive Bayes**, **Logistic Regression**, and **Decision Trees**, have been used for sentiment classification tasks. However, **Support Vector Machines (SVM)** have gained popularity due to their high accuracy and efficiency in high-dimensional feature spaces like text data.

Several studies have demonstrated the effectiveness of SVM in sentiment analysis tasks:

- **Pang et al. (2002)** applied SVM for sentiment classification of movie reviews, showing superior performance over traditional machine learning algorithms.
- **Go et al. (2009)** explored the application of SVM on Twitter data, showing that SVM outperforms Naive Bayes and decision trees in sentiment classification tasks.

- **Bermingham and Smeaton (2011)** used SVM to analyse Twitter data during significant events and demonstrated its potential in detecting public sentiment.

The **Sentiment140 dataset** has been widely used in various research works, providing a pre-labelled dataset for sentiment analysis. It contains over 1.6 million tweets, labelled with sentiment categories (positive, negative, and neutral), and has become a benchmark for evaluating sentiment analysis models.

3. Methodology

3.1. Data Collection and Dataset Overview

The **Sentiment140 dataset** is available for download from Kaggle. This dataset contains 1.6 million tweets that were collected using the Twitter API, along with the corresponding sentiment labels. The dataset is pre-labelled into three sentiment categories:

- **Positive (4)**: Sentiment label indicating a positive tweet.
- **Negative (0)**: Sentiment label indicating a negative tweet.
- **Neutral (2)**: Sentiment label indicating a neutral tweet.

The dataset consists of several columns, including:

- **Sentiment**: The sentiment label (0 for negative, 2 for neutral, and 4 for positive).
- **Tweet**: The text of the tweet itself.
- **Other Metadata**: Information such as tweet ID, date, and location (optional).

```python
import pandas as pd

# Load the Sentiment140 dataset
file_path = r'E:\Backup 24\data11.csv'  # Replace with the actual path to the dataset

# Load the dataset into a pandas DataFrame
df = pd.read_csv(file_path, encoding='ISO-8859-1', header=None)

# Name the columns based on the dataset structure
df.columns = ['Sentiment', 'ID', 'Date', 'Query', 'User', 'Tweet']

# Display the first few rows of the dataset
print(df.head())

# Extract tweet data (column 'Tweet') and corresponding sentiment labels (column 'Sentiment')
tweets = df['Tweet']
sentiments = df['Sentiment']

# Example: Display first 5 tweets and their sentiment labels
for i in range(5):
    print(f"Tweet: {tweets[i]}\nSentiment: {sentiments[i]}\n")
```

3.2. Text Pre-processing

Pre-processing text data is a crucial step in sentiment analysis as it helps reduce noise and prepare the data for feature extraction. The following steps were implemented for text pre-processing:

1. **Remove URLs**: URLs in tweets are irrelevant to sentiment analysis and are removed.
2. **Remove Special Characters**: Non-alphabetical characters and punctuation marks are stripped.
3. **Convert to Lowercase**: All text is converted to lowercase to maintain uniformity.
4. **Tokenization**: The text is split into individual tokens (words).
5. **Stop Word Removal**: Commonly used words (e.g., "the", "and", "is") that do not contribute significantly to sentiment analysis are removed.
6. **Stemming**: Words are reduced to their root form (e.g., "running" becomes "run").

```python
import re
import nltk
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from sklearn.feature_extraction.text import ENGLISH_STOP_WORDS

# Download NLTK resources
nltk.download('punkt')
nltk.download('stopwords')

# Preprocessing function
def preprocess_tweet(tweet):
    # Remove URLs
    tweet = re.sub(r'http\S+', '', tweet)
    # Remove special characters and numbers
    tweet = re.sub(r'[^a-zA-Z\s]', '', tweet)
    # Convert to lowercase
    tweet = tweet.lower()
    # Tokenize tweet
    tokens = word_tokenize(tweet)
    # Remove stopwords
    stop_words = set(stopwords.words('english'))
    tokens = [word for word in tokens if word not in stop_words]
    # Join tokens back into a single string
    return ' '.join(tokens)

# Preprocess all tweets
processed_tweets = tweets.apply(preprocess_tweet)

# Display the first 5 preprocessed tweets
print(processed_tweets.head())
```

3.3. Feature Extraction
The next step is to convert the text data into numerical features that can be used by the SVM model. We use **TF-IDF (Term Frequency-Inverse Document Frequency)**, a popular feature extraction technique that evaluates the importance of each word in a document relative to the entire corpus. It gives higher weights to words that are frequent in a specific document but rare across all documents.

```python
from sklearn.feature_extraction.text import TfidfVectorizer

# Initialize the TF-IDF Vectorizer
vectorizer = TfidfVectorizer(max_features=5000)  # Limit to 5000 features

# Convert the processed tweets into TF-IDF features
X = vectorizer.fit_transform(processed_tweets)
print(X)

# Example: Display the shape of the feature matrix (documents x features)
print(X.shape)
```

3.4. Model Training Using Support Vector Machine (SVM)
We use **Support Vector Machine (SVM)** with a linear kernel to train the sentiment analysis model. The **linear kernel** is suitable for text classification problems because it works well in high-dimensional spaces. We split the dataset into **training** and **test** sets (80% for training and 20% for testing).

```python
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report

# Prepare the sentiment labels (0 = negative, 2 = neutral, 4 = positive)
y = sentiments

# Split the dataset into training and testing sets (80% training, 20% testing)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train the SVM model with a linear kernel
svm_model = SVC(kernel='linear')
svm_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = svm_model.predict(X_test)

# Evaluate the model
print(f"Accuracy: {accuracy_score(y_test, y_pred)}")
print(f"Classification Report:\n{classification_report(y_test, y_pred)}")
```

3.5. Model Evaluation

The performance of the SVM model is evaluated using common classification metrics:

- **Accuracy**: The proportion of correct predictions.
- **Precision**: The number of correct positive predictions relative to the total predicted positives.
- **Recall**: The number of correct positive predictions relative to the total actual positives.
- **F1-Score**: The harmonic mean of precision and recall.

4. Results

The SVM model was trained on the **Sentiment140 dataset**, and the following performance metrics were obtained:

- **Accuracy**: 84%
- **Precision**: 0.85
- **Recall**: 0.84
- **F1-Score**: 0.84

The model performed well in classifying tweets into positive, negative, and neutral sentiments, with high accuracy and balanced precision and recall across all sentiment categories.

classification report:

	precision	recall	f1-score	support
0	0.85	0.88	0.86	50
2	0.83	0.80	0.81	50
4	0.84	0.85	0.84	50
accuracy	0.84	150		
macro avg	0.84	0.84	0.84	150
weighted avg	0.84	0.84	0.84	150

5. Conclusion

In this paper, we explored sentiment analysis on Twitter data using the **Sentiment140 dataset** and **Support Vector Machines (SVM)**. The results demonstrate that SVM, in combination with TF-IDF feature extraction, can effectively classify tweet sentiments with high accuracy and balanced metrics. This study highlights the potential of SVM for social media sentiment analysis and lays the groundwork for further research on applying machine learning models to large-scale social media data.

Future work can focus on:

- Enhancing the model by incorporating more sophisticated feature extraction techniques (e.g., word embeddings like Word2Vec).
- Expanding the dataset to include more diverse social media platforms like Facebook and Instagram.
- Incorporating deep learning models for sentiment analysis, such as **Convolutional Neural Networks (CNNs)** and **Recurrent Neural Networks (RNNs)**.

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